Web Appendix

A Additional Tables

Table A1: SAS school participation by region

Region	Year of SAS introduction	No. of schools
Tarapaca	2017	128
Antofagasta	2018	143
Atacama	2018	124
Coquimbo	2017	546
Valparaiso	2018	766
O'Higgins	2017	499
Maule	2018	659
Biobio	2018	1135
Araucania	2018	983
Los Lagos	2017	817
Aysen	2018	73
Magallanes	2016	61
Metropolitana	2019	–
Los Rios	2018	396
Arica y Parinacota	2018	91

Note: Details on the number of schools participating in each region are taken from table 1 in 2018 database manual given by SAE. The school sample consists of all schools across all grades that participated in SAS.

Table A2: Summary statistics: The match between enrollment and SIMCE files

Variables	N	Mean	Std. dev.	Min.	Max.
Enrollment 2015	265093	–	–	–	–
Matched with SIMCE eight 2014	242574	–	–	–	–
% with valid background info	84.84	–	–	–	–
Mother's education	175208	11.66	3.64	0	22
Father's education	170831	11.67	3.79	0	22
Family income index	176958	4.96	3.50	1	15
Enrollment 2016	259037	–	–	–	–
Matched with SIMCE eight 2015	235884	–	–	–	–
% with valid background info	84.41	–	–	–	–
Mother's education	173888	11.74	3.68	0	22
Father's education	165191	11.67	3.88	0	22
Family income index	173737	5.14	3.52	1	15
Enrollment 2017	255400	–	–	–	–
Matched with SIMCE sixth 2014	239341	–	–	–	–
% with valid background info	80.04	–	–	–	–
Mother's education	168422	12.66	3.67	1	22
Father's education	161247	12.74	3.91	1	22
Family income index	169738	4.94	3.55	1	15
Enrollment 2018	246937	–	–	–	–
Matched with SIMCE eight 2017	229371	–	–	–	–
% with valid background info	87.03	–	–	–	–
Mother's education	172283	12.01	3.63	0	22
Father's education	165711	11.92	3.83	0	22
Family income index	172304	5.60	3.61	1	15
Enrollment 2019	246115	–	–	–	–
Matched with SIMCE sixth 2016	232182	–	–	–	–
% with valid background info	81.04	–	–	–	–
Mother's education	165184	12.09	3.58	0	22
Father's education	157139	11.92	3.72	0	22
Family income index	163323	5.40	3.62	1	15

Notes: Table shows the extent of match between the enrollment and the SIMCE files from 2015 to 2019. We use parents' education and family income index as student background variables, so this Table also lists the number of cases for which we obtained non-missing data for these variables. SIMCE reports a household income index that ranges between 1 and 15. The mean income index of ∼5 corresponds to an income between $400,000 - $500,000 (in Chilean Pesos).

Table A3: The policy adoption date and the pre-existing levels of school segregation

VARIABLES	Year of implementation (1)
Segregation (pre-SAS)	0.120
	[0.475]
Constant	-1.376
	[0.903]
Observations	327
R-squared	0.120
Covariates	y

Note: *** p<0.01, ** p<0.05, * p<0.1. This table explains that the start date of SAS is not correlated with pre-SAS segregation. Segregation pre-SAS corresponds to the level of school segregation in 2015 computed using the Duncan index.

Table A4: SAS and residential segregation

VARIABLES	SAS dummy (D_{rt}) (1)
Residential segregation	-0.000
	[0.002]
Constant	0.452***
	[0.138]
Observations	1,623
R-squared	0.104
Covariates	y

Note: *** p<0.01, ** p<0.05, * p<0.1. This table shows that SAS dummy is not correlated with residential segregation.

Table A5: Residential segregation: Using access to police station

VARIABLES	Duncan index (1)
SAS dummy (D_{rt})	-0.039***
	[0.013]
Residential segregation	-0.003
	[0.002]
SAS dummy (D_{rt})×Residential segregation	0.011***
	[0.003]
Constant	0.140*
	[0.073]
Observations	1,623
R-squared	0.150
Region FE	y
Year FE	y
Covariates	n

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. The residential segregation variable is constructed as access to police stations in this Table.

B Travel Distance

In collaboration with the Ministry of Education of Chile, we use the HERE geocoder API for geocoding of the residential addresses of the complete ninth-grade cohort in Chile in 2018.[15] Table B1 provides details on the quality of geo-referencing. We tried forward geocoding for 240,634 ninth graders in 2018. However, the administrative enrollment files did not have the first address line for about 29% of ninth graders. For the remainder 71% with valid house addresses, we can determine precise latitude longitude for about 61% of the sample. The API is not able to locate geo-coordinates for 10% of students. We use municipality centroids as the location proxy for the students who had a missing first line of address in the enrollment file, or the geocoder API failed to locate the coordinates.

To obtain precise measures of student's travel duration to basic amenities, we employ the Open Source Routing Machine (OSRM) service for travel time calculation. The OSRM package uses the open street maps data to measure the shortest travel time using a car, bicycle, or foot between two location coordinates. As Figure B1 shows, our measure of travel time or travel distance using the open street maps has much higher precision than geodetic measures of distance employed in related research.[16]

We also illustrate in Figure B2 that it is pertinent to examine the distance to schools using the actual travel time. Its panels A and B suggest that two schools that are almost equidistant based on straight line measures of distance have very different travel distances as the latter takes into account the road network.

We define an amenity to be accessible if the driving time is within an hour for a student. Since the regression analysis is done at the municipality level, we construct measures of variation for access to amenities for ninth graders within a municipality in the year 2018. For example, Figure 4 in the main text shows that access to amenities varies to a large extent across municipalities in Chile.

[15] For complete details on the HERE geocode API refer to the documentation provided in https://developer.here.com/documentation.

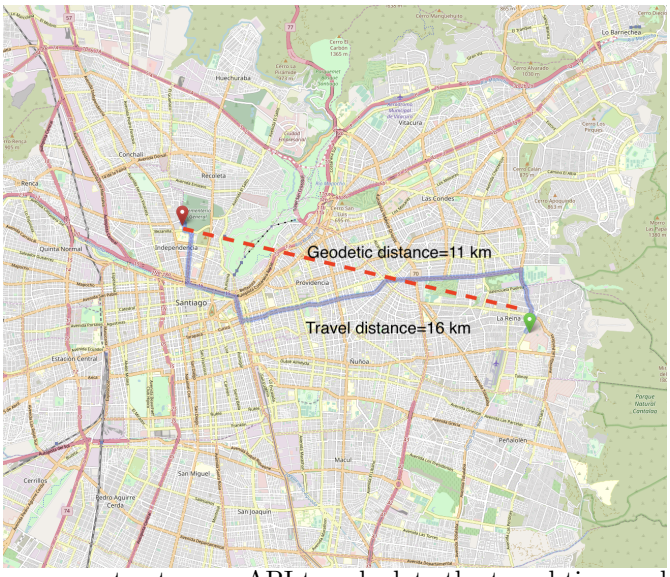
[16] The geodetic measure calculates the distance between two location coordinates taking into account the curvature of the earth. Consequently, geodetic distance is different from linear euclidean measures.

Table B1: Quality of forward geocoding of ninth grade cohort

	N	%
Geo-coordinates located by API	146161	60.74
Geo-coordinates not located by API	24673	10.25
Enrollment file does not record first line of house address	69800	29.01
Total observations	240634	100

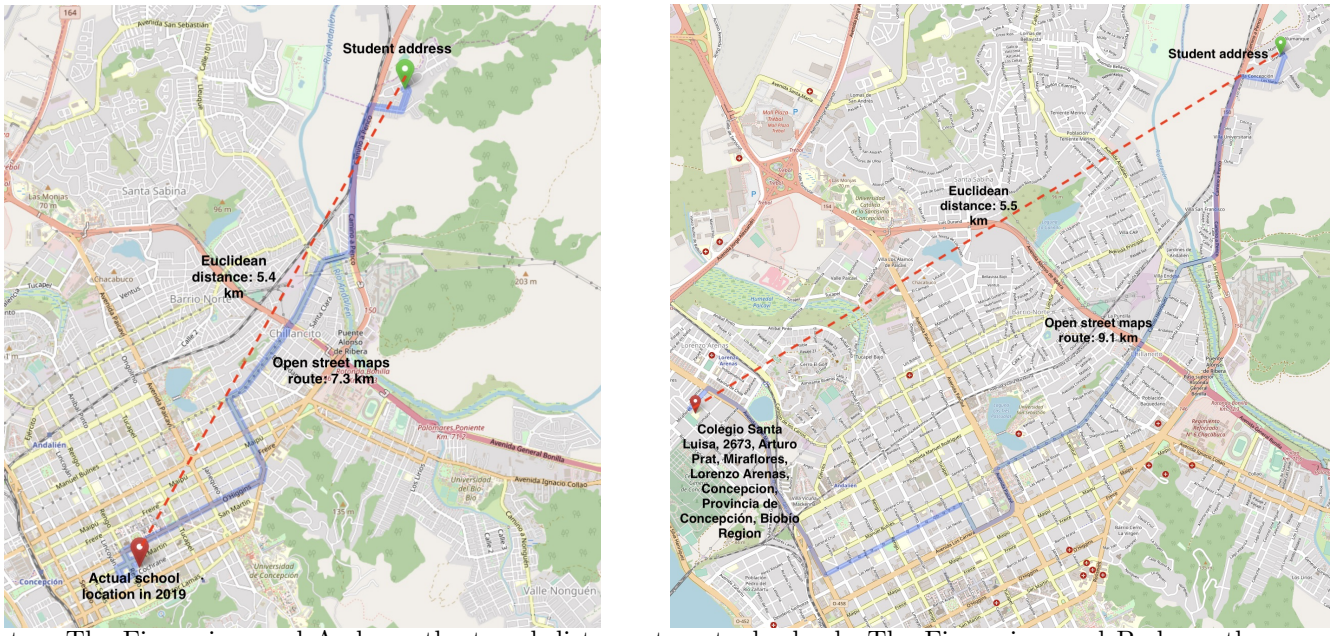
Notes: Student enrollment files provide complete residential addresses for the entire universe of ninth-graders. We use the HERE geocoder API for forward geocoding these addresses and obtaining the geo-coordinates. Student geo-coordinates are required for travel time calculation to school.

Figure B1: Travel distance and travel time



Notes: We use open street maps API to calculate the travel time and distance by car between two geo coordinates in Santiago. The geodetic distance underestimates the actual commuting time as it does not take into account the road network for distance analysis.

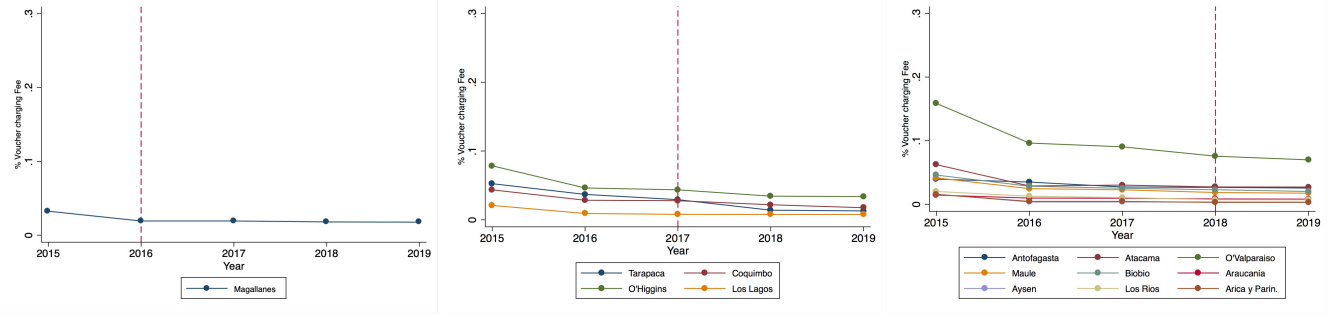
Figure B2: Student travel time to school: comparison of travel distance vs. euclidean or geodetic distance



Notes: The Figure in panel A shows the travel distance to actual school. The Figure in panel B shows the travel distance to another school in the neighborhood.

C The elimination of co-payment vs. the implementation SAS.

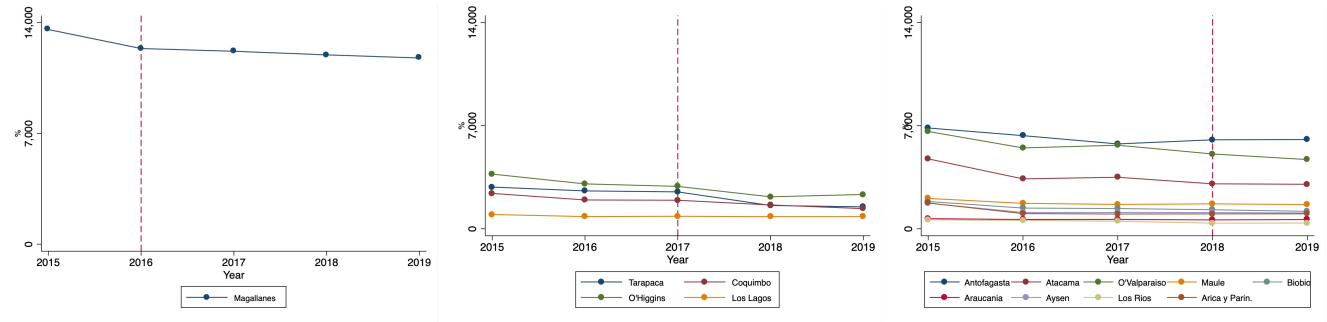
Figure C1: The association between the fraction of schools within school districts charging fees and the implementation of SAS



A. SAS in 2016 B. SAS in 2017 C. SAS in 2018

Notes: Panel (A) displays the fraction of voucher schools charging fee for the region where students participated in SAS in 2016, panel (B) displays it for regions where students participated in SAS in 2017. Finally, panel (C) displays the results for regions where SAS was launched in 2018.

Figure C2: The association between average school sees (co-payment levels in CLP) within school districts and the introduction of SAS



A. SAS in 2016 B. SAS in 2017 C. SAS in 2018

Notes: Panel (A) displays the average co-payment of voucher schools charging fees for the region where students participated in SAS in 2016 (Chilean pesos of 2015), panel (B) displays it for regions where students participated in SAS in 2017. Finally, panel (C) displays the results for regions where SAS was launched in 2018.

Table C1: Difference-in-Difference: Average School Fees (co-payment levels) as the Outcome Variable

VARIABLES	(1)	(2)	(3)	(4)
SAS dummy (D_{rt})	0.773	0.568		
	[1.332]	[1.355]		
% of enrollment in public pre-SAS		-29.674***		-29.671***
		[10.042]		[10.042]
% enrollment in voucher pre-SAS		-18.501**		-18.498**
		[9.335]		[9.335]
Intensity of SAS (I_{rt})			0.989	0.747
			[1.516]	[1.542]
Constant	16.127*	36.586***	16.106*	36.566***
	[9.573]	[13.464]	[9.565]	[13.462]
Observations	735	735	735	735
R-squared	0.238	0.281	0.238	0.281
Region FE	y	y	y	y
Year FE	y	y	y	y
Additional covariates	n	y	n	y

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. Column (1) and (2) use SAS dummy as the treatment variable, while column (3) and (4) use intensity as treatment variable. The outcome variable is school fee (scaled by per 1000 Chilean Pesos) charged by the voucher schools. We show that changes in school fee during the implementation of the program are orthogonal to the SAS.

Table C2: Difference-in-Difference: The impact of SAS by the fraction of voucher schools with co-payment within the school district

VARIABLES	(1) 0%	(2) $< 10\%$	(3) $< 60\%$
SAS dummy(D_{rt})	-0.006	-0.002	0.000
	[0.011]	[0.010]	[0.006]
Constant	0.011*	0.008	0.108*
	[0.006]	[0.006]	[0.064]
Observations	755	960	1,605
R-squared	0.169	0.133	0.129
Region FE	y	y	y
Year FE	y	y	y
Additional covariates	n	n	n

Notes: ***p<0.01, ** p<0.05,* p<0.1. Standard errors clustered at municipality in square brackets. In specification (1) we repeat the regression for average treatment effect of SAS restricting to school districts with no voucher schools charging copayment. In columns (2) and (3) we restrict to school districts with less than 10% of voucher schools charging copayment, and less than 60% of schools charging copayment, respectively.